Farm technical efficiency and myths of training and technology using an application of DEA single bootstrap: empirical evidence from Gilgit-Baltistan, Pakistan.

Recebimento dos originais: 24/05/2021
Aceitação para publicação: 09/11/2021

Nadeem Akhtar Khan (Corresponding Author)
Doctoral Researcher Applied Economics
School of Economics and Finance
Xi'an Jiaotong University Shaanxi P.R. China
Department of Agriculture Gilgit-Baltistan Pakistan
E-mail: **nadeemakhtar2001@gmail.com**

Xiu-yun Yang
Professor
School of Economics and Finance
Xi'an Jiaotong University Shaanxi P.R. China
E-mail: **yangxiuyun@mail.xjtu.edu.cn**

Naeem Akhtar
Postgraduate Researcher
Department of Mathematics
Università degli Studi di Salerno Italy
E-mail: **naeemnoor49@gmail.com**

Waheed Ali
Doctoral Researcher Applied Economics
School of Economics and Finance
Xi'an Jiaotong University Shaanxi P.R. China
E-mail: **aliwaheed@stu.xjtu.edu.cn**

Hadi Hussain
Doctoral Researcher Applied Economics
School of Economics and Finance
Xi'an Jiaotong University Shaanxi P.R. China
E-mail: **hussainhadi@stu.xjtu.edu.cn**

Najabat Ali
Post-doctoral Researcher
School of Finance and Economics
Jiangsu University Zhenjiang China
E-mail: **alinajabat@hotmail.com**

Abstract

Augmenting efficiency and productivity at the farm level requires an infusion of the new knowledge and technology compatible with the local social, cultural and economic environment. The current study evaluated the farm technical efficiency and impact of training and technology on apricot farms technical efficiency. This study adopted the single bootstrap DEA with algorithm one using externally estimated efficiency scores to assess the various determinants of efficiency. The study observed substantial inefficiency across the apricot farm, and efficiency can be raised by reducing inputs by 18% with the current output level. Additionally, findings indicate that more scale efficient farmers and majority farmers confronted with the decreasing return to scale. Further, the study noted a positive and statistically significant association between training, technology and apricot farms technical inefficiency. In contrast, family and hired labour exhibit adverse and significant effects on inefficiency across the farms.

Keywords: Bootstrap. DEA. Technical Efficiency.

1. Introduction

Data envelopment analysis (DEA) is a non-parametric approach that assumes a linear programming pathway to rank the performance of any entity. The non-parametric does not restrict the functional form by enacting assumptions and permits heterogeneous production technologies (Badunenko and Mozharovskyi, 2016). Nevertheless, this study assumed the bootstrap framework illustrated by Simar Wilson (1998, 2000, and 2007) to DEA to postulate the statistical inferences. This study is principally interested in measuring the input-oriented overall and pure technical efficiency using CCR and BCC models of the DEA framework. Secondly, the current study adopted the Simar Wilson (2007) approach using a single bootstrap procedure (Algorithm 1) to assess the impact of training and technology and other determinants on various efficiency levels across the apricot farms.

Bootstrap in DEA measures the uncertainty of conventional statistical interference, proposed by Simar Wilson (1998) later on modified this method to account for the influence of environmental attributes on technical efficiency. Further, algorithms in Simar Wilson (2007) methodology in the second stage allow making valid inferences about the traditional approaches unable to make a valid inference with undesirable regression outcomes (Keramidou, Mimis, & Pappa, 2011; Colino, Benito-Osorio, & Rueda-Armengot, 2014). Simar Wilson (2007) pointed out serial correlation and biasness in the DEA efficiency estimates, undermining the validity of traditional inferences in two-step frameworks.

In order to overcome these issues, Simar Wilson (1998) proposed bootstrap treatment to obtain reliable inferences within the defined frameworks presenting efficiency scores and approximating standard errors and confidence intervals for these scores concurrently. Since the current literature on the analysis of farm technical efficiency in agriculture, traditional stage DEA has not considered its inferential attributes and requires caution while designing comprehensive policy options led by these outcomes. An alternative procedure, bootstrap, was conceived by Simar Wilson (2007) by adopting single bootstrap regression (algorithm 1) and double bootstrap (algorithm 2). How every this study preferred algorithm one over algorithm. Very few studies adopted the single bootstrap to measure the farm technical efficiency to the best of our knowledge. Since the single bootstrap (algorithm 1) allows consistent inferences within the assumed empirical framework and measure standard errors and confidence intervals (Karimov, 2013; Vígh et al., 2018). Further, the double bootstrap procedure is a complex and expensive estimation process, and computational procedures can also be a burden (see for details, Simar & Wilson, 2007; Singbo, Lansink, & Emvalomatis, 2014; Singbo & Lansink, 2010).

2. Literature Review

Farrell (1957) coined technical efficiency to refer to the extent to which a firm produces optimum possible production with a given combination of input factors or, in other words, by employing the least possible bundle of aspects of production to produce a given level of output. The traditional DEA approach has been used in analyzing farm technical efficiency for a long time. For example, Ayaz et al. (2011), Shaheen et al. (2011), and Murtaza & Thapa (2017) adopted the two-stage input-oriented DEA to assess the factors of technical efficiency of cauliflower and apple growers in Pakistan, respectively.

When applying DEA, it is pretty challenging to draw statistical conclusions about technical efficiency due to several causes; since technical efficiency estimates are derived from the samples. However, the feature of the traditional DEA approach is deterministic; the efficiency is still calculated comparative to estimates instead of the actual frontier. The scores of efficiency estimated from restricted samples are subject to the sampling discrepancy of the estimated frontier (Simar and Wilson, 1998; Badunenko and Mozharovskyi, 2016).

Existing studies considering the technical efficiency of apricot farms adopting the single bootstrapping DEA is missing in the literature. However, current literature on the two-stage DEA approach noted the prevalence of various estimation frameworks in the second stage. For instance, Gunduz et al. (2011) employed a two-stage DEA and Tobit regression to assess the technical efficiency and factors affecting the technical efficiency of apple and apricot farms in Turkey. Furthermore, Uçar and Engindeniz (2016) investigated the economic aspects of fresh apricot production in Turkey. Except for these two studies, no other study was conducted on the technical efficiency of apricot previously. Two-stage DEA and two-limit Tobit, Truncated regression, and OLS were widely adopted in agriculture and aquaculture. For instance, Dhungana et al. (2004), Nowak et al. (2016), Asghar et al. (2018), and Nanii et al. (2020) adopted the DEA and Tobit to analyze the technical efficiency in various agricultural farms in Europe, Ghana, Nepal, and Pakistan respectively.

Similarly, Daadi et al. (2014), Mukhtar et al. (2018), Balogun et al. (2018), and Molua et al. (2019) adopted the SFA & DEA technique to compute the technical efficiency of mango, pearl millets, and pineapple farms in Ghana, Nigeria, and Cameroon respectively. However, the adoption of single and double bootstrapping DEA was not joint in estimating the technical efficiency of agricultural farms since its development. Nevertheless, some earlier studies on the farm technical efficiency adopting the double bootstrapping DEA approach are (Balcombe et al., 2008; Karimov, 2013), who analyzed the efficiency sources of rice farming and productive efficiency of watermelon and potato in Bangladesh and Uzbekistan.

Since the estimated technical efficiency measures are excessively positive, the DEA estimate of the production set is essentially a fragile subset of the actual production set under standard assumptions of basic DEA (Badunenko and Mozharovskyi, 2016; Simar and Wilson, 2000). Simar and Wilson (1998, 2000) presented smoothed bootstrapping into the DEA approach to provide a statistical base to non-parametric frontier models to deal with these shortcomings.

The recent studies adopted the double bootstrap DEA approach on the technical efficiency of various farms across the agriculture sector. For instance, (Ullah and Perret, 2014) studied cotton farms' technical and environmental efficiency in Pakistan. Similarly, Zhuang et al. (2016) used double bootstrap DEA to analyze the technical efficiency of Chinese litchi farms. Moreover, a recent study by, Işgın et al. (2020) adopted a single and double bootstrap method to study cotton farms in Turkey. Similarly, Yobe et al. (2020) adopted the Simar and Wilson methodology to measure the financial efficiency of agricultural cooperatives in South Africa. Danso-Abbeam et al. (2020) studied the technical efficiency of cocoa farmers in Ghana to explain gender differential in farm efficiency. Recent studies by Li et al. (2019); Ton et al. (2018); Anh Ngoc et al. (2018), and; Iliyasu et al. (2016) adopted two-stage single and double bootstrap DEA methodology in aquaculture for bias correction in the measuring of technical efficiency.

3. Conceptual Framework

As we stated formerly, the core theme of the study is to measure the technical efficiency of apricot farms and the impact of training and technology imparted among the apricot growers in the area under study. In this context, based on a thorough review of relevant literature, we developed a hypothetical model to illustrate the impact of training and technology on the apricot farms' technical efficiency. The transfer and adoption of advanced knowledge and technology induce innovation and transformation in agriculture has been pivotal pathways to augment productivity, efficiency, ensure food security, economic development in the rural area and alleviate poverty and vulnerability across the small scale farming communities (Abdul-Rahaman, Issahaku, & Zereyesus, 2021). Additionally, the energetic involvement of the farmers in the formal and informal training settings stimulates learning, transfer and dissemination of farm technology among the farmers (Asiabaka, 2002; FAO, 2001).

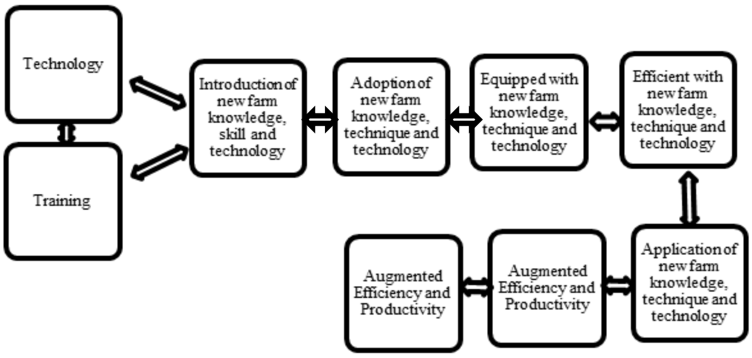

Figure 1: **Conceptual Framework**
Authors' construction

Similarly, Sjakir et al. (2015) noted the significant effects of the training program under farmer field school on the knowledge gain and adoption of new technology and significant productivity improvement. Amara et al. (1999) found a significant contribution of conservation technologies in improving technical efficiency. In contrast, Stewart et al. (2015) noted some positive impacts of training on household farm income but were insignificant statistically.

According to our paramount understanding, no such past empirical studies in Pakistan examined the relationship among the apricot growers' training, technology, and technical efficiency. The observed gap is recognized through a thorough review of related literature. We applied the single bootstrapping based on the algorithm one suggested by Simar & Wilson (2007) to this novelty, examining the impact of training and technology on-farm technical efficiency of apricot growers. This study has the following objectives: 1) To determine the technical and scale efficiency of apricot farmers in Gilgit-Baltistan, Pakistan. 2) Categorize the behaviour of returns to scale. 3) To determine the intensity of training and technology on the technical efficiency of apricot farms. 4) To determine the factors affecting the technical efficiency of apricot farmers. Moreover, this study developed a hypothetical regime based on the following assumptions; first, the efficiency differentials are absent among the apricot farmers. Second, no degree of association exists among the technical efficiency and training, technology. The remaining parts of this study include the following four sections along with sub-sections. The first part illustrates the methods and materials. The second demonstrates the methodology, and the third part presents the arguments on results and discussions. Finally, the fourth part offers a conclusion and policy implication.

4. Methods and Material

4.1. Study area

This cross-sectional appraisal was conducted among the apricot growers from three districts, namely Hunza, Nagar, and Kharmang, in Pakistan's Gilgit-Baltistan region. These three districts of the Gilgit-Baltistan region were chosen due to their enormous potential in apricot production and the population's livelihood dependence on apricot farming and associated activities. The survey was carried out between March 2018 and April 2019 using a structured questionnaire. The data was gathered from the trained apricot farmers by the Department of Agriculture Gilgit-Baltistan between 2012 and 2017. The primary objective of this project was to build the capacities of apricot growers in the selected districts through training and transfer of new technologies and the dissemination of advanced knowledge and skills. The project offered various activities on applying pruning, grafting, rootstock management, preparation of organic fertilizers and pesticides, harvesting, grading, drying technology, packing, and marketing. The project also helped farmers identify the potential markets for their apricot products at national and international levels.

Figure 2: Map of Gilgit-Baltistan (Hunza-Nagar, Kharmang)
Source: JICA Project for improvement of value-added fruit product in Gilgit-Baltistan

4.2. Sample Size and Data Collection

This empirical study engaged a structured questionnaire instrument to collect the data on apricot production, costs of inputs, revenue from apricot, farm area, number of apricot trees, and labour applied. Additionally, information related to training received, technology transfer, and other indicators related to socio-economic attributes of the apricot farm were included. The data on apricot farm households, population, and other statistics were acquired from the relevant district administration and agriculture department to calculate the appropriate sample size. The district administration and agriculture departments identified the 3225 apricot farming households in the area under study.

We adopted a random sampling approach to collect the sample data using structured questionnaire-based face-to-face interviews from apricot growers. Random sampling is the most suitable sampling procedure because each sample has an equal chance of selection (Secker et al., 1995); we adopted Taro Yamane, (1974) formula for random sampling to determine the appropriate sample size.

$$n = \frac{N}{1+Ne^2} \text{ -- } (6)$$

Whereas n denotes sample size, N represents the total population, and e indicates sampling error.

$$n = \frac{3225}{1+3225*(0.07)^2} = 192 \quad (7)$$

A sample of 192 individual apricot growers was determined after implementing the scientific technique; however, we collected 230 representatives from the area under study, and 222 questionnaires were found reliable and appropriate.

4.3. Methodological Approach

4.3.1 Empirical design

Apricot farmers in the Gilgit-Baltistan region of Pakistan confronted various problems while managing their apricot orchards. This study supposed that apricot growers follow an input orientation (cost minimization) approach. Generally, farmers have to face the challenge of engaging the best minimum combination input factors among scarce resources without compromising the current level of yields. We supposed that any apricot farm produced a single output of apricot employing a combination of multiple factor inputs. This study used sample data from the 222 apricot growers. This study adopted both CCR and BCC under an input-oriented DEA framework to measure the performance of apricot farms in the area under consideration following Cooper et al. (2007) and later by Murtaza & Thapa (2017). We estimated the orchard efficiency in comparison with the other orchards in the sample by employing the input-oriented CCR model as under:-

$$\text{minimize } \theta - \left(\sum_r s_r^+ + \sum_i s_i^-\right)$$

Subject to subsequent restrains

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta_0 x_{i0,} \; i = 1,2,3 \ldots, m$$

$$\sum_{j=i}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro}, \; r = 1,2,3, \ldots, s \quad (1)$$

$$\lambda_j, s_i^-, s_r^+ \geq 0; \; \forall_i, j, r$$

Where x_{ij} represents the factor inputs and y_{rj} denotes the output of the farmers. While λ_j is the vector of weights represent the efficient farmers assisting in identifying the inefficient farmer or the distance of the inefficient farmer from the frontier. On the other hand, θ denotes the index of farmer technical efficiency spreading between 0 and 1. As we earlier elucidated CCR based data envelopment or primal model undertakes a constant return to scale (CRS) regime. On the other hand, a proportionate variation will occur in output due to specific changes in input employed.

Similarly, the constant return to scale (CRS) explains crop production's composite or overall technical efficiency. However, according to Ullah and Perret (2014), farm production assumes variable return (VRS) to scale due to the attribute of potential economies of scale. We obtained overall technical efficiency by adopting CCR based data envelopment, which consists of two parts.

Overall TE= Pure technical efficiency (TEBCC) × scale efficiency (SE) or

TECCR = TEBCC × scale efficiency (SE) --------------------------------------(2)

Here TEBCC represents the farmer's management capabilities through the management efficiency, and SE denotes the distance between overall TE and TEBCC that explains whether a farmer is operating at a maximum output level (Heidari et al., 2012). Moreover, the seminal work of Charnes et al. (1978) CCR based DEA was extended through the addition of $\Sigma_j\ \lambda_j$ =1 for the variable return to scale regime known as the BCC model postulated by the Banker et al. (1984). Hence the input-oriented BCC model illustrated using the following expression: -

$$\text{minimize } \theta - (\textstyle\sum_r s_r^+ + \sum_i s_i^-) \text{---(3)}$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta_0 x_{i0,}\ i = 1,2,3 \ldots, m$$

$$\sum_{j=i}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro},\ r = 1,2,3, \ldots, s$$

$$\sum_j \lambda_j = 1$$

$$\lambda_j, s_i^-, s_r^+ \geq 0; \text{ for all } i, j, r$$

The BCC model and other fractions of overall TE (TEccr) pure technical and scale efficiencies were illustrated in equation (3). The scale efficiency score ranges from 0 to 1, which implied that a farmer is operating at an optimum level of output or constant return to scale. Additionally, if the scale efficiency score is less than 1, the farmer is deemed to be operating under an increasing return to scale. Further, it indicates that a proportionate rise in input leads to a greater than proportional increase in output. On the other hand, if a commensurate surge in factor inputs returns less than a proportionate increase in production implies decreasing return to scale (DRS). The farms operating under decreasing turn to scale exhibit scale inefficiencies suggest a transfer of resources to the firms operating under increasing returns to scale to augment the average productivity and avoid the wastage of scarce resources (Heidari et al., 2012; Umanath & Rajasekar, 2013; Wang et al., 2013; Murtaza and Thapa, 2017).

The farm management capabilities of farmers and availability, easy access to inputs, and support facilities play a pivotal role in determining the technical efficiencies in farm production (Wang et al., 2013; Poudel et al., 2015; Murtaza and Thapa, 2017). Similarly, as we formerly highlighted the key farm-related derivers of farm productivity. Therefore, this study employed the Simar Wilson (2007) approach in the second phase to analyze the impact of the selected variables on the technical efficiency of apricot farmers.

4.3.2 Bootstrapping procedure

This empirical investigation employs the two-stage DEA approach to obtain the results. Initially, we calculated the technical efficiency of the apricot farms under the CCR framework. Similarly, the use of the CCR model will provide in-depth insight by accommodating both (CRS) constant returns to scale and (VRS) variable returns to scale (Stewart et al., 2016). Multiple estimation errors can affect the farm's performance, whereas the DEA approach does not represent any statistical noise and variation in efficiency scores causes uncertainty (Karimov. A, 2013). To cope with sampling error, Simar & Wilson (2007) proposed bootstrapping efficiency scores. On the other hand, Green (2007) also suggests bootstrapping to deal with the absence of the statistical foundation, which arises from DEA's construct of frontiers from samples, not from the population.

In the second stage, this study adopts the Simar Wilson (2007) two-stage efficiency analysis framework with a single bootstrap approach to regress the determinants of farm technical efficiency. The application of truncated regression and bootstrapping in the second stage can generate valid results, and data is generated by the data generating process (Simar & Wilson, 2007; Stewart et al., 2016; Khan et al., 2018; Li et al., 2019;). We applied Algorithms 1 with 2000 iteration to obtain the results because both Algorithms 1 and 2 can give similar results (Karimov, 2013; Vígh et al., 2018). Hence the steps involved in single bootstrapping presented in the following manner:-

Table 1: Step in Algorithm 1

Step 1: Assuming novel data of the amount of production, Yj, and inputs, Xj, j=1,...,n (all positive values) calculate DEA efficiency score δj.
Step 2: Employed the technique of maximum likelihood to acquire an estimation of β and a compute in the truncated regression of on Zj (Eq. (3)) employing m < n observations where.
Eq. (3) :
Step 3: Loop over the subsequent three phases [3.1]–[3.3] 2000 times to get a set of bootstrap estimations
[3.1] For each j=1...,n, draw εj from the distribution with left-truncation.
[3.2] Over again, for every j=1...n, calculate.
[3.3] To compute the truncated regression of Zj, yielding estimates employ the maximum likelihood technique.
Step 4: To build the estimated confidence intervals for every set of β and σε, employ bootstrap values in step 3.

Thus equation (5) presents a general function to be estimated in the following framework:-

$$\delta_j = z_j\beta + \varepsilon_j \quad (4)$$

$$\delta_j = \beta_* + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7 + \beta_8 \quad (5)$$

$$\delta_j = \beta_* + \beta_1 tec + \beta_2 ta + \beta_3 fwh + \beta_4\, hlwh + \beta_5\, edu + \beta_6\, gdr + \beta_7\, fs + \beta_8 mkt \quad (6)$$

This study employed one dependent and eight explanatory variables to estimate the second stage Simar & Wilson (2007) efficiency analysis single bootstrapping after a thorough review of relevant literature. A detailed description and descriptive statistics of the variables included in the second stage are presented in table 5. Additionally, all employed explanatory variables were regressed against the externally estimated TE (CRS) and PTE (VRS) scores to assess the influence of the determinants of efficiency.

5. Results and discussions

5.1. Description of variables (efficiency component)

The emphasis of this study is to look into the effects of training and technology on the technical efficiency of apricot farms in Pakistan. We initiated this empirical analysis by estimating the technical efficiency adopting the conventional farm production factors. This empirical study employed one output and five inputs factors of production based on the previous literature to determine the technical efficiency of apricot farms. Conventionally, farm technical efficiency can be measured by involving farm output and factor inputs such as farm produce, planting area, number of plants, labour, and water cost (Madou, 2011; Wang et al., 2018). This study adopts the farm income (Monetary Value) as an output variable instead of physical output (Quantity) following the empirical literature (Zhuang et al., 2016; Li et al., 2019; Yang et al., 2020).

Table 2: Descriptive Statistics of variables (efficiency component)

Variable	Mean	Std.Dev	Minimum	Maximum
Output Variables				
Apricot Farm Income	42375.00	44439.00	4100.00	278450.00
Input Variables				
Farm Area	3.80	4.50	0.20	30.00
NAT	22.60	25.40	2.00	160.00
Hired labour	2.07	5.02	0.00	32.00
Family Labor	87.00	73.67	12.00	560.00
Cost of Water	222.38	337.27	0.000	2500.00

Authors own creation from survey data (2019).

5.2 Description of variables (determinants of technical efficiency)

The second stage employed eight factors (table 3) to evaluate the intensity of influence over apricot farm technical efficiency. As the core aim of this novelty is to assess the nature of the relationship among the training, technology, and technical efficiency of apricot farmers. Under this project, specific training and technologies were disseminated among the apricot farmers to improve productivity, efficiency, and apricot farm income. Training attended represents the participation in a variety of training about apricot farm management, rootstock management, harvesting, grading, drying, packing, and marketing of apricots. Technology in this study refers to the combination of new proto-type dryers, organic fertilizer, and pesticides introduced by the project among the apricot growers.

We employed other variables such as work hours devoted by the family members of apricot households and labour hours contributed by hired labour in line with Madou's (2011) study. Further, we used the level of education to gauge the qualification of the head of the family and on the average middle (8^{th} standard) and maximum master level of education noted among the apricot farmers. The gender represents the gender of the family head. The female head of the family was denoted by 0, while the male was indicated by1. Family size defines the number of family members in apricot farm households, and the average family size was consists of 9 members.

In comparison, the large family was comprised of 24 members in the area under consideration. New marketing channels are essential in determining the farm's level of profitability (Naseer et al., 2019) and the project also helped the farmers to discover new avenues to market their apricot production. Therefore, keeping in view the importance of this intervention, we have included the marketing variable (dummy).

Table 3: Descriptive Statistics (determinants of technical efficiency)

Variable	Mean	Std-Dev	Minimum	Maximum
Technology	6.80	4.50	3.20	33.00
Training	0.95	0.21	0.00	1.00
Family Working Hours	86.95	73.70	12.00	560
Hired Labor Working Hours	2.07	5.00	0.00	32.00
Education Level	2.20	1.50	0.00	6.00
Gender	0.65	0.50	0.00	1

Family Size	9.00	4.60	1.00	24.00
Marketing	3.10	1.50	0.00	5.00

Authors own estimation from survey data (2019)

5.3. Estimation of technical efficiency scores (First Stage)

This study calculated the efficiency scores of apricot farms by adopting the CCR-DEA input-oriented model under the assumption of (TE) constant returns to scale regimes. The findings of this analysis presented in Table 4 show the means and distribution of efficiency scores. These scores indicate the substantial inefficiencies among the apricot producers in the area under consideration. The mean technical efficiency (CRS) of apricot farms was 0.82, which implied that each apricot farm was operating at an 82% level of production efficiency and its distribution was between 0.53 and 1. The mean efficiency (CRS) implied that apricot farms were inefficient and needed to improve their efficiency.

Moreover, the mean of pure technical efficiency (VRS) was 0.86, and the range was confined between 0.62 and 1. Apricot farms under the PTE (VRS) were found inefficient, as indicated by the mean value of efficiency (VRS) in table 3 is slightly higher than TE (CRS). Similarly, this estimation finds 0.95 mean scale efficiency, and the range of efficiency levels was between 0.68 and 1 among the sampled apricot farms. There were variations among TE (CRS), PTE (VRS), and scale efficiency (SE); however, the mean of scale efficiency was higher than technical efficiency and pure technical efficiency at 0.95.

Table 4: Summary statistics efficiency score

Variable	Mean	Std. Dev	Minimum	Maximum
TE(CRS)	0.82	0.08	0.53	1
PTE(VRS)	0.86	0.08	0.62	1
Scale Efficiency	0.95	0.06	0.68	1

Authors own estimation from Survey data (2019)

5.4 Analysis of returns to scale

Apparent variations caught the scale inefficiency in technical efficiency (CRS) and pure technical efficiency (VRS). To estimate the scale efficiency, we have divided technical efficiency over pure technical efficiency. Figure 2 reveals the findings of the evaluation of returns to scale for individual apricot farms by adopting the method presented in the former part. The individual farms were categorized regarding their respective returns to scale. The results revealed that 80% apricot farm was under the decreasing return to scale (DRS), 15% were under increasing return to scale (IRS), and the remaining 5% were operating under constant returns to scale (CRS) regime.

5.5. Distribution of efficiency scores

The statistics presented in Table 5 show the frequency distributions and ranges of efficiency scores of technical efficiency (CRS), pure technical efficiency (VRS), and scale efficiency of apricot farms. About 5.04% of apricot farms were found fully efficient under the TE (constant returns to scale), and 11.26% were operating between 90% and 99%. In contrast, 43.24% of farms were fell in between 0.80 and 0.89 efficiency scores. Further, about 34.68% of farms were operating in between 0.70 and 0.79 efficiency scores. In contrast, 4.94% of farmers were in the range of 0.60 and 0.69. The remaining 0.45% of farms fell in the range of 0.50 and 0.69 technical efficiency scores.

Table 5: Range of Efficiency Scores

Efficiency Score Range	Technical Efficiency (CRS)		Pure Technical Efficiency (VRS)		Scale Efficiency	
	Frequency	Per cent	Frequency	Per cent	Frequency	Per cent
0.50 - 0.59	1	0.45	0	0	0	0
0.60 – 0.69	11	4.94	3	1.40	2	0.90
0.70 - 0.79	77	34.68	43	19.40	3	1.35
0.80 - 0.89	96	43.24	98	44.14	27	12.16
0.90 –0.99	25	11.26	50	22.52	126	56.76
1	12	5.04	28	12.61	64	28.83

Authors own estimation from Survey data (2019)

Further, PTE scores (variable returns to scale) exhibited that about 12.61% of apricot farms were fully efficient, which means that these farms were operating at a 100% efficiency level. Similarly, 22.52% of farms were ranged between 0.90 and 0.99. 44.14% of farmers were found between 0.80 and 0.89 efficiency scores under variable returns to scale. Further, 19.40% and 1.40% of farms were under the efficiency score between 0.70 to 0.79 and 0.60 to 0.69.

About 64 sampled apricot farms were fully efficient under the scale efficiency comparatively greater than 12 farms and 28 farms under TE (CRS) and PTE (VRS). Moreover, 126 farms were found in a range of 0.90-0.99. Furthermore, the remaining 27 and 3 farms were found between 0.80 to 0.89 and 0.70 to 0.79 efficiency scores. The remaining two farms were under the ambit of 0.60 to 0.69 efficiency scores. The variation of technical efficiency in the study area implied that the apricot farmers could not utilize appropriate production mechanisms and input applied. Further, these outcomes were found consistent with the results of **(**Murtaza and Thapa, 2017; Sherzod et al., 2018; Molua et al., 2019**)** that differentials between TE (CRS) and PTE (VRS) reveal the scale inefficiencies.

The overutilization of input resources causes inefficiency in decision-making units (DMUs), so to curtail inefficiency, farmers are required to reduce the cost of inputs applied without decreasing the current level of apricot production. However, the efficiency of the decision-making unit (DMUs) can be improved by the appropriate utilization of technical inputs in the production process (Arru et al., 2019). It was implied from the analysis of returns to scale that most apricot farmers were operating under the decreasing returns to scale due to inefficient employment of inputs. In other words, the proportion of output obtained by the apricot growers was less than the proportion of input applied. These returns to scale were consistent with findings of (Bielik M Rajčániová, 2012; Ilahi et al., 2019), and 77% and 74.5% of farms were under decreasing returns to scale, respectively.

5.6. Determinants of apricot farm technical efficiency.

This estimation demonstrates the apricot farm's technical efficiency presented in tables 6 and 7. In this estimation, determinants of technical efficiency were regressed against the overall technical efficiency (CRS) and pure technical efficiency (VRS) efficiency scores separately. Table 6 presents the estimation of technical efficiency (CRS), and the model was found statistically significant at a level of 1%. This empirical estimation processed 222 DMUs, out of which 12 DMUs were found efficient under TE (CRS), respectively. Further, the coefficient of training (TA) and Technology (Tec) variable was positive and statistically significant at a 5% and 1% significance level, respectively.

Further, the coefficient of family labour (FWH) variables was statistically significant at a 5% significant level and negatively related to technical efficiency. Similarly, the coefficient of hired labour (HLWH) variable was also statistically significant at a 1% level of significance and negatively associated with technical efficiency. The coefficient of education indicator was significant statistically at a 5% significance level but shows a negative relationship with the technical efficiency of apricot farms.

Table 6: Simar & Wilson (2007) regression model 1

Variables	Observed. Coefficients	Bootstrap Std. Errors	Z	95% confidence interval lower	95% confidence interval upper
TE(CRS)					
TA	0.0545**	0.0220	2.48	0.0134	0.0977
Tec	0.0150***	0.0028	5.26	0.0094	0.0201
FWH	-0.0010***	0.0007	-6.12	-0.0013	-0.0007
HLWH	-0.0019**	0.0010	-2.04	-0.0037	-0.0001
Edu	-0.0064**	0.0032	-2.03	-0.0126	-0.0001
Gdr	-0.0171	0.0100	-1.71	-0.0360	0.0022
FS	0.0011	0.0010	1.06	-0.0010	0.0032
Mkt	0.0040	0.0032	1.21	-0.0025	0.0102
_cons	0.7518***	0.0270	27.92	0.6700	0.8060
Sigma	0.0652***	0.0034	18.93	0.0571	0.0706
Number of obs	210				
Efficient DMUs	12				
Bootstrap. reps	2000				
Wald chi2(8)	55.47				
Prob > chi2(8)	0.0000				
Algorithm	1				

Authors own estimation from Survey data (2019)
*, **, *** specify the significance level at 10%, 5% and 1% respectively

Table 7 shows the results for the estimated parameters of the bootstrap truncated regression PTE (VRS) model. The positive and negative sign associated with estimated parameters indicates the decreasing and increasing effects on efficiency scores. The model was found significant statistically at a 5% significance level. Under the present estimation framework, this estimation processed 222 DMUs, out of which 28 DMUs were efficient, and other remaining 194 DMUs were found inefficient. However, unexpectedly six parameters out of eight were insignificant except for training (TA) and education (Edu). The coefficient of training (TA) parameter was statistically significant at a 5% significance level and positively associated with the efficiency scores. Further, the coefficient of education (Edu) was also statistically significant but negatively related to the efficiency scores.

Table 7: Simar & Wilson (2007) regression model 2

Variables	Observed. Coefficients	Bootstrap Std. Errors	Z	95% confidence interval lower	95% confidence interval upper

TE(VRS)					
TA	0.0600**	0.0245	2.40	0.0079	0.1034
Tec	0.0001	0.0038	0.01	-0.0070	0.0080
FWH	0.0002	0.0002	0.99	-0.0002	0.0006
HLWH	-0.0015	0.0011	-1.38	-0.0037	0.0007
Edu	-0.0081**	0.0036	-2.29	-0.0153	-0.0010
Gdr	-0.0140	0.0117	-1.20	-0.0370	0.0085
FS	0.0004	0.0013	0.30	-0.0021	0.0031
Mkt	0.0014	0.0040	0.36	-0.0060	0.0087
_cons	0.7955	0.0300	26.92	0.7381	0.8546
Sigma	0.0705	0.0041	17.19	0.0608	0.0768
Number of obs	194				
Efficient DMUs	28				
Bootstrap. reps	2000				
Wald chi2(8)	16.86				
Prob > chi2(8)	0.0316				
Algorithm	1				

Authors own estimation from Survey data (2019)
*, **, *** specify the significance level at 10%, 5% and 1% respectively

5.7. Discussions

This study observed significant inefficiency among the apricot growers' despite participation in the training program and introduction of technology. Nevertheless, the study outcomes concerning inefficiency were in line with the findings of Idris et al. (2013), who examined the technical efficiency of pineapple growers trained under the specific program and noted inefficiencies. Further, Balogun et al. (2018) assessed the efficiency of pineapple farmers who participated in the agriculture development program and noted inefficiencies among the examined farms.

The core variable training found positive and significant at a 5% level of significance against the CRS and VRS based efficiency scores. Further, this occurrence implied that training tends to raise the inefficiencies among the apricot growers. In contrast, Yang et al. (2020), Sharma et al. (2017) and Murtaza and Thapa (2017) observed contradicting outcomes and found significant effects of training in augmenting farm efficiencies. Additionally, this posture training may be due to the incompatibility of apricot farmers and their lack of resilience towards adaptability and application of skill and knowledge received since training plays a strategic role in imparting new knowledge skill and technology among farmers and strengthens the decision-making capabilities in farm management which consequently, rise resource use efficiency (Karimov, 2014; Noor & Dola, 2011). However, Mgendi et al. (2021) argued that training alone might not improve the productivity of farming communities across the developing economies and suggested considering both farm and non-farm factors.

Similarly, the coefficient of technology (Tec) variables was significant and positively associated with inefficiency under TE (CRS) framework while found insignificant but positive under PTE (VRS). The former conduct of technology implied that technology, in this case, causes inefficiency among the apricot growers in the area under consideration. Notwithstanding, on the contrary, Jimi et al. (2019), Abdulai et al. (2018), Abdullahi et al. (2015) and Parke (2013) observed contradicting outcomes that technology was found significant in improving technical efficiency among the various group of farms. However, Torkamani (1996) highlighted the possible attributes behind the observed outcome of technology that disseminating new technology may not give the desired output if the existing knowledge is not competent. Similarly, Kalirajan (1996) discussed and farmed opinion as; augmented efficiency is essential for increasing productivity and adopting new technology is worthless unless the utilization of current technology maximized at the optimum level. On the other hand, the findings concerning the technology were in line with the study of Yang et al. (2020), who observed sort of outcomes similarly while evaluating the impact of technology on technical efficiency.

The coefficients of family and hired labour parameters were negative and significant under the CRS estimation regime while found insignificant under the VRS framework. The negative sign denotes the counter effects on technical inefficiency; thus, family and hired labour reduce technical inefficiency in our case. These findings were consistent with a study by Onumah et al. (2013). In contrast, some study observed contradicting outcomes; for instance, Kuwornu et al. (2013) found that excessive use of family labour and less employment of hired labour causes resource use inefficiency. Joseph (2014) postulated similar arguments about the inefficient use of family and hired labour while analyzing the determinants of technical efficiency. At the same time, education was found insignificant but positively associated the scale efficiency (SE). These results were consistent with the findings of Wadud and White (2000) that found an inverse effect of education efficiency scores but found insignificant statistically. However, later studies, for example, using DEA double bootstrapping approach, Balcombe et al. (2008) found positive and statistically significant effects under CRS and VRS specifications. In contrast, Coelli et al. (2002) found a positive influence of education on technical efficiency but was statistically insignificant.

6. Conclusion and Policy

In this study, we adopted the DEA with the algorithm one based single bootstrap approach to assess the technical efficiency and enlighten the variations and sources of technical efficiency for a sample of apricot growers in the Gilgit-Baltistan region Pakistan. From policy consideration, this study finds the following crucial conclusions.

The findings showed a significant variation in TE (CRS) efficiency scores, PTE (VRS), and scale efficiency. The mean technical efficiency suggests 18% inefficiency among the apricot farmers and could be improved by amending production inputs—the analysis of returns to scale revealed that 85% of farmers were performing under the decreasing returns. Moreover, 15% increasing returns, and 5% of farmers were under the constant returns to scale. Moreover, returns to scale presumed that most of the farmers realized less output than inputs applied in the study area. These findings revealed a substantial efficiency gap among the farmers analyzed.

Secondly, this study evaluated the determinants of the technical efficiency of sample apricot farms and revealed positive and significant effects of training and technology on the technical inefficiency of apricot growers. However, the phenomena of training and technology in other farms have been studied except for the apricot farms under consideration and elsewhere. Additionally, the parameter family working hours was significant and negatively associated with the apricot farm's technical efficiency. Similarly, the coefficient of hired labour indicated a negative and statistically significant effect on technical efficiency. Further, the current study noted the inverse relationship of hired labour with the technical efficiency of apricot farms. In contrast, previous studies reportedly disclosed the peculiar effects of family and hired labour on the farm's technical efficiency.

Moreover, the study noted the substantial inefficiency among the apricot growers emanating from various factors. Similarly, the study's findings found the majority of farms operating under the decreasing returns to scale. In this context, farmers under decreasing returns to scale should readjust their inputs utilization plan to avoid wasting input resources. Importantly, accelerating resource use efficiency and strengthening the capacities of apricot growers would be pivotal to augment the technical efficiency. Furthermore, in this context-appropriate interventions from relevant stakeholders to boost apricot farmers' managerial and technical capabilities are proposed. Keeping in view the inverse effects of training and technology on apricot farms technical efficiency, the provision of training and technology should be compatible with the local environment so that favourable impacts of training and technology could be realized. Additionally, this study proposed future longitudinal research to unearth the attributes of training and technology in determining the long-run differentials in the apricot farms' technical efficiency over time.

7. References

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8. Acknowledgement

This research project was funded by my supervisorXiu-yun Yang Professor through the National Natural Sciences Foundation of China (Grant No.71673215, No.71974158).